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Entropy and the Emotional Brain: Overview of a Research Field

Beatriz García-Martínez, Antonio Fernández-Caballero and Arturo Martínez-Rodrigo

Abstract

During the last years, there has been a notable increase in the number of studies focused on the assessment of brain dynamics for the recognition of emotional states by means of nonlinear methodologies. More precisely, different entropy metrics have been applied for the analysis of electroencephalographic recordings for the detection of emotions. In this sense, regularity-based entropy metrics, symbolic predictability-based entropy indices, and different multiscale and multilag variants of the aforementioned methods have been successfully tested in a series of studies for emotion recognition from the EEG recording. This chapter aims to unify all those contributions to this scientific area, summarizing the main discoveries recently achieved in this research field.

Keywords: Emotion recognition, Electroencephalographic recordings, Entropy metrics, Nonlinear analysis, Survey

1. Introduction

Emotions are essential in our daily lives, with an enormous repercussion on perception, cognition, learning and rational decision-making processes [1]. As a result, the affective neuroscience has emerged with the purpose of studying the influence of emotions on areas like psychology, philosophy or neurobiology, among many others [1]. The emotional states defined in the literature range from a few basic emotions [2] to several complex emotions created as combinations of the basics [3]. These emotional states can be classified according to different models, being the circumplex model of Russell one of the most widely used [4]. This bidimensional model distributes all the existing emotional states according to two emotional parameters, namely valence and arousal. Valence represents the degree of pleasantness or unpleasantness produced by an emotional stimulus, whereas arousal measures the activation or deactivation that a stimulus provokes. The location of each emotional state in the circumplex model is determined by its level of both dimensions, as shown in **Figure 1**.

Emotions also play a key role in human communication and interaction processes. Nevertheless, the human-machine interfaces (HMIs) are still not able to identify human emotional states. In a digital society in which those systems are daily introduced in multiple ordinary scenarios, it becomes crucial to supplement this lack of

Figure 1.
Circumplex model of Russell for classification of emotions based on their level of valence and arousal.

emotional intelligence of HMIs. In this sense, the aim of the Affective Computing science is to endow those systems with the capability to automatically detect and interpret human emotions and decide which actions to execute accordingly, thus improving the interactions between people and machines [5, 6].

The detection of emotional states can be conducted by means of the assessment of bodily reactions to emotional stimuli, for which different physiological variables can be measured and analyzed. One of the most widely studied in the last years is the electroencephalography (EEG), which represents the electrical activity generated in the brain due to neural connections [7]. The selection of EEG recordings instead of other physiological signals is justified by the fact that the brain generates the first impulse against any stimulus, and then it is spread to the rest of peripheral systems through the central nervous system. In this sense, EEG signals represent the activity of the source of the emotional response, whereas the rest of physiological variables can be considered as secondary effects of the brain's performance [8]. As a consequence, the number of works focused on the analysis of EEG time series for emotions detection has notably increased in the last years [9].

The evaluation of EEG recordings has been traditionally conducted from a linear perspective, especially in the frequency domain, studying features such as the spectral power or the asymmetry between the two brain hemispheres in different frequency bands [10]. However, the brain activity is far from being considered linear. Contrarily, neural processes follow a completely heterogeneous and nonstationary performance even at both cellular and global level [11]. With this respect, the application of linear algorithms may not report a complete description of the brain's behavior [12]. For this reason, nonlinear methodologies have been widely applied for discovering underlying information unrevealed by traditional linear techniques [13]. Indeed,

nonlinear indices have already outperformed the results derived from the application of those linear algorithms for the evaluation of various mental processes, including the recognition of emotions [13].

Among the different nonlinear methodologies that can be found in the literature, entropy indices have been widely applied in the context of emotions recognition with EEG recordings [14]. Entropy represents the rate of information reported by a time series, describing the nonlinear characteristics of a nonstationary system [15]. Hence, entropy metrics become promising tools for the assessment of the chaotic dynamics of a nonstationary system such as the brain. Indeed, in the literature many studies have applied these nonlinear methodologies for the identification of emotional states from EEG recordings. The present manuscript summarizes the main discoveries of the last years in the scientific field of emotions recognition from EEG signals with entropy indices.

2. Entropy indices

Entropy was firstly defined in thermodynamics, referring to the distribution probability of molecules in a fluid system [15]. In information theory and signals analysis, this concept was adapted by Shannon, who defined entropy as a measure of the information provided by a time series, describing its complexity, irregularity or unpredictability [16]. With respect to the EEG analysis, many entropy indices have been introduced and successfully applied for the study of various physical and mental disorders, like epilepsy [17], Alzheimer [18], autism [19] or depression [20], among others. As a result of the valuable outcomes, entropy metrics have also been introduced in the research field of emotions recognition from EEG recordings [14]. The following subsections give a brief mathematical description of the entropy metrics mainly applied for emotions detection.

2.1 Regularity-based entropy indices

The irregularity of a signal represents the rate of repetitiveness of patterns, reaching higher values for non-repetitive and disordered time series, and lower for sequences with a high rate of occurrence [21]. One of the regularity-based entropy metrics widely used is the approximate entropy (ApEn), which evaluates the probability of having repetitive patterns and assigns a non-negative number to each sequence in terms of its repetitiveness, with lower values for more recurrent patterns [22]. Mathematically, ApEn is computed as

$$\text{ApEn}(m, r) = C^m(r) - C^{m+1}(r), \quad (1)$$

where $C^m(r)$ and $C^{m+1}(r)$ are the correlation integrals that represent the likelihood of having two sequences matching for m and for $m + 1$ points, respectively, within the threshold r [22]. Nevertheless, ApEn also considers the self-matching of each sequence, thus influencing on the final result. Therefore, the sample entropy (SampEn) was developed to address this issue [23]. SampEn eliminates the self-matching and makes results independent of the value of the vector length m selected. If $B^m(r)$ is the probability that two patterns match for m points, and $B^{m+1}(r)$ is the probability that two patterns match for $m + 1$ points, defined to exclude self-matches, then SampEn is calculated as

$$\text{SampEn}(m, r) = -\ln \left[\frac{B^{m+1}(r)}{B^m(r)} \right]. \quad (2)$$

Moreover, quadratic sample entropy (QSampEn) emerged as an improvement of SampEn to make it insensitive to the value of the threshold r chosen for its calculation [24]. This independence of the parameter r is achieved by simply adding the term $\ln(2r)$ to the SampEn equation:

$$\text{QSampEn}(m, r) = \text{SampEn}(m, r, N) + \ln(2r). \quad (3)$$

2.2 Predictability-based and symbolic entropy indices

The predictability of a nonstationary system is related to its stable and deterministic evolution in time. Most of the entropy metrics for predictability measurement are symbolic indices that convert the original signal into a sequence of discrete symbols to form sequences [25]. After this symbolization, the evaluation of the predictability of a time series can be carried out with multiple techniques. The most commonly used is the Shannon entropy (ShEn), which quantifies the predictability of a signal in terms of the probability distribution of its amplitudes [16]. The mathematical expression of ShEn is

$$\text{ShEn}(m) = -\sum_{i=1}^m p(x_i) \cdot \ln(p(x_i)), \quad (4)$$

being $p(x_i)$ the probability of appearance of each symbolic sequence x_i of length m .

The Rényi entropy (REn) is a generalization of ShEn that is also widely used for the quantification of underlying dynamics in symbolized signals [26]. Concretely, REn provides a better characterization of some rare and frequent ordinal sequences, and it is defined as

$$\text{REn}(m, q) = -\frac{1}{1-q} \ln \sum_{i=1}^m p(x_i)^q, \quad (5)$$

being q ($q \geq 0$ and $q \neq 1$) the bias parameter that enables a more accurate characterization of a nonlinear signal [26]. Indeed, ShEn is the particular case of REn for $q = 1$, thus being REn a more flexible index than ShEn [26].

The version of ShEn for continuous random variables, called differential entropy (DEn), has received growing interest in the last years [27]. This entropy index can be expressed as

$$\text{DEn}(X) = -\int_X f(x) \log(f(x)) dx \quad (6)$$

where X is a random signal and $f(x)$ is its probability density function. In the case of time series governed by the Gauss distribution $N(\mu, \sigma^2)$, being μ and σ its mean and variance, respectively, DEn can be defined as

$$\text{DEn}(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx = \frac{1}{2} \log(2\pi e \sigma^2). \quad (7)$$

As EEG signals follow a Gaussian distribution after the application of a band-pass filtering approach, the DEn of each sub-frequency band previously obtained by a Fast Fourier transform can be obtained according to the aforementioned equation [27].

Another widely used predictability-based entropy metric is permutation entropy (PerEn), which is a fast and insensitive to noise metric that evaluates the order of the symbols within a pattern [28]. Briefly, the original time series is symbolized to obtain ordinal sequences x_i that are associated with $m!$ permutation patterns κ_i . Considering $p(\pi_k)$ as the probability of appearance of each permutation pattern, PerEn can be then computed by means of ShEn:

$$\text{PerEn}(m) = -\frac{1}{\ln(m!)} \sum_{k=1}^{m!} p(\pi_k) \cdot \ln(p(\pi_k)). \quad (8)$$

One of the limitations of PerEn is that it only considers the order of the symbols in a pattern, without taking into account their amplitudes. This limitation has been recently solved by means of the introduction of amplitude-aware permutation entropy (AAPE) [29]. This improvement of PerEn computes the probability $p^*(\pi_k)$ of appearance of patterns evaluating the average absolute and relative amplitudes of the symbolic sequences, and applying an adjustment coefficient to weight those parameters. Finally, AAPE is calculated in a similar manner as PerEn [29]:

$$\text{AAPE}(m) = -\frac{1}{\ln(m!)} \sum_{k=1}^{m!} p^*(\pi_k) \cdot \ln(p^*(\pi_k)). \quad (9)$$

Another option for the assessment of predictability of a time series is the spectral entropy (SpEn) [30]. In this case, the spectral power of a determined frequency is computed and normalized with respect to the total power, which gives a probability density function p_f . SpEn is then computed through ShEn or REn [30].

2.3 Multilag and multiscale entropy indices

The time series generated by nonlinear and nonstationary systems like the brain usually present highly complex dynamics derived from different simultaneous mechanisms that operate in multiple time scales [31]. As a result, the brain behavior cannot be completely described by means of single-scale methods. Therefore, multiscale variations of the aforementioned entropy metrics have been introduced with the purpose of revealing undiscovered information related to the multiscale nature of the EEG recordings. For the computation of multiscale entropy (MSE), the original signal $x(n)$ is firstly decomposed into coarse-grained time series $y^{(\kappa)}$, with κ as the scale factor, as follows:

$$y^{(\kappa)} = \frac{1}{\kappa} \sum_{i=(j-1)\kappa+1}^{j\kappa} x(i), \quad 1 \leq j \leq \frac{N}{\kappa}. \quad (10)$$

Therefore, all the previously defined entropy indices can be computed in a multiscale form for the coarse-grained series as defined above.

Another multiscale option is the wavelet entropy (WEn), which makes use of the decomposition of the original signal in different scales by means of the wavelet

transform [32]. After the decomposition of the time series, the probability distribution p_j of the energy at each decomposition level is computed. Finally, WEn is estimated through ShEn:

$$\text{WEn} = - \sum_{j=1}^q p_j \cdot \ln(p_j). \quad (11)$$

On the other hand, the characteristics of the autocorrelation function of some signals require the consideration of a lag or time delay τ for a correct quantification of the complexity and nonlinear dynamics of the time series. In this sense, multilag entropy approaches are helpful to reduce the influence of the autocorrelation function for a proper characterization of a nonlinear signal [33]. One of those multilag approaches is the permutation min-entropy (PerMin), which is a symbolic time-delayed improvement of PerEn [34]. Starting from a generalization of PerEn through replacing ShEn by REn, the Rényi permutation entropy (RPE) is obtained as

$$\text{RPE}(m, q, \tau) = \frac{1}{\ln(m!)} \cdot \frac{1}{1-q} \ln \left(\sum_{k=1}^{m!} p^\tau(\pi_k)^q \right). \quad (12)$$

Finally, PerMin is obtained in the limit $q \rightarrow \infty$ and presents the following expression:

$$\text{PerMin}(m, \tau) = - \frac{1}{\ln(m!)} \ln \left(\max_{k=1, 2, \dots, m!} [p^\tau(\pi_k)] \right). \quad (13)$$

3. Literature overview

In the literature, there are various studies that have applied regularity-based entropy measures for emotions detection with EEG recordings. A brief summary of those works is presented in **Table 1**, with information about the year of publication, the experimental design (including the number of emotions detected, subjects, EEG channels and type of stimulus), the features extracted, the classification models implemented, and the results obtained in each case. As can be observed, the interest in these metrics started growing in 2014, especially computing ApEn and SampEn for the detection of a number of emotions ranging between 2 and 4. In many cases, the signals analyzed were extracted from the publicly available Database for Emotion Analysis using Physiological Signals (DEAP), which consisted on a total of 32 healthy subjects watching emotional videoclips during the registration of their EEG with 32 channels [47]. Hence, different studies tested their methods on the same EEG recordings, thus allowing a direct comparison of the results obtained [37–39, 41, 42, 48]. The rest of works had different experimental designs. In terms of the classification models, support vector machines (SVM) were selected in most of the cases [35, 37, 38, 40, 43–45]. The outcomes derived from these studies presented a classification accuracy (Acc) ranging between 73% and 95%, being the frontal and parietal brain regions the most relevant for the detection of emotional states with these regularity-based entropies.

On the other hand, the predictability-based entropy indices have been the most applied for the assessment of different emotional states from EEG recordings. The

Ref. (Year)	Experimental design	Features	Classifier	Results
[35] (2011)	2 emotions, 15 subjects, 5 EEG channels, images	ApEn + others	SVM ¹	Acc = 73.25%
[36] (2014)	Depression, 60 subjects, 24 EEG channels, eyes open/closed, no stimuli	ApEn + others	—	Higher irregularity for healthy than for depressed
[37] (2014)	4 emotions, DEAP ²	SampEn	SVM	Acc = 80.43%
[38] (2016)	4 emotions, DEAP	SampEn + others	SVM	Acc = 94.98% (two classes) and 93.20% (four classes)
[39] (2016)	2 emotions, DEAP	SampEn, QSampEn + others	DT ³	Acc = 75.29%
[40] (2017)	3 emotions, 44 subjects, 31 EEG channels, images	ApEn + others	SVM	Acc = 75.5%
[41] (2018)	Valence and arousal, DEAP	SampEn + others	MLP ⁴ , DST ⁵	Acc = 87.43% (arousal) and 88.74% (valence)
[42] (2018)	4 emotions, DEAP	SampEn + others	PSAE ⁶	Acc = 93.6%
[43] (2018)	4 emotions, 10 subjects, 14 EEG channels, film clips	ApEn + others	SVM, DBN ⁷	Acc = 87.32%
[44] (2019)	4 emotions, 8 subjects, 12 EEG channels, music	ApEn, SampEn + others	SVM, C4.5, LDA ⁸	Acc = 84.91% (valence) and 89.65% (arousal)
[45] (2020)	3 emotions, SEED ⁹	DySampEn ¹⁰	SVM	Acc = 84.67%
[46] (2021)	2 emotions, DEAP	CSampEn ¹¹	—	More coordination in parietal and occipital

¹SVM: Support vector machine.
²DEAP: Database for emotion analysis using physiological signals.
³DT: Decision tree.
⁴MLP: Multi-layer perceptron.
⁵DST: Dempster-Shafer theory.
⁶PSAE: Parallel stacked autoencoders.
⁷DBN: Deep belief networks.
⁸LDA: Linear discriminant analysis.
⁹SEED: SJTU emotion EEG database.
¹⁰DySampEn: Dynamic SampEn.
¹¹CSampEn: Cross-sample entropy.

Table 1.
Studies of emotions recognition from EEG recordings with regularity-based entropy indices.

main studies that have used these entropy metrics for that purpose are included in **Tables 2** and **3**. It can be observed that only a few works studied these indices between 2011 and 2015 [49–52, 63]. Nevertheless, the interest in these predictability measures has notably increased since 2017 until nowadays. More precisely, DEn is the predictability-based metric that has gained a considerable visibility since 2018, thus **Table 3** only includes studies based on the application of DEn. The rest of predictability-based entropy metrics, i.e. ShEn, REn, SpEn, and permutation indices, are contained in **Table 2**. It is interesting to note that the majority of these works in **Table 2** analyzed the EEG signals contained in the DEAP database, whereas only a few

Ref. (Year)	Experimental design	Features	Classifier	Results
[49] (2011)	5 emotions, 20 subjects, 24 and 62 EEG channels, videos	ShEn, SP ¹	LDA, KNN ²	Entropy better than linear. Acc = 83.04% with 62 channels
[50] (2013)	Stress, 13 subjects, 3 EEG channels, eyes closed, no stimuli	REn + others	ANOVA ³	Lower complexity in stress than in calmness
[51] (2015)	4 emotions, 8 subjects, 20 EEG channels, audiovisual stimuli	ShEn, REn	MC-LSSVM ⁴	Acc = 84.79%
[52] (2015)	4 emotions, 25 subjects, 3 EEG channels, music	SpEn	SVM, KNN, CFNN ⁵	Acc = 93.66% (valence) and 93.29% (arousal)
[53] (2017)	2 emotions, DEAP	PerEn, AAPE, QSampEn	SVM	Acc = 81.31%
[54] (2017)	Valence and arousal, DEAP	SpEn, ShEn	LSSVM ⁶ , D-RFE ⁷	Acc = 78.96% (arousal) and 71.43% (valence)
[55] (2017)	4 emotions, DEAP	SpEn, ShEn + others	Three-stage decision method	Acc = 86.67%
[56] (2018)	Arousal and valence, DEAP	SpEn, spectral and statistics	SVM, KNN, NB ⁸	Spectral and statistics better than SpEn
[57] (2018)	2, 3, 4 and 5 emotions, DEAP	REn + others	SVM	Acc = 73.8–86.2%
[58] (2018)	Depression, 213 subjects, 3 EEG channels, sounds	ShEn, SpEn + others	KNN	Acc = 79.27%
[59] (2019)	4 emotions, DEAP	ShEn, SpEn + others	LSSVM	Acc = 65.13%
[60] (2019)	4 emotions, DEAP	ShEn, PerEn + others	SVM	Best results with PerEn
[61] (2020)	2 emotions, DEAP	CEn ⁹ , QSampEn	SVM	Acc = 80.31%
[62] (2020)	4 emotions, DEAP	SpEn, ShEn + others	SVM, NB, ANN ¹⁰	Acc = 98.7% with ANN
[48] (2021)	4 emotions, DEAP	AAPE, PerMin + others	SVM	Acc = 96.39%

¹SP: Spectral power.
²KNN: K-nearest neighbor.
³ANOVA: Analysis of variance.
⁴MC-LSSVM: Multiclass least-square support vector machine.
⁵CFNN: Cascade-forward neural network.
⁶LSSVM: Least-square support vector machine.
⁷D-RFE: Dynamical recursive feature elimination.
⁸NB: Naive Bayes.
⁹CEn: Conditional entropy.
¹⁰ANN: Artificial neural network.

Table 2.
Studies of emotions recognition from EEG recordings with predictability-based entropy indices (ShEn, SpEn, REn, PerEn, AAPE).

tested those metrics with different experiments. As for the regularity-based indices, the number of emotions identified in works in **Table 2** ranged from 2 to 4, and only one study recognized 5 emotional states [49]. In terms of the classifiers implemented, SVM approaches were preferred over other models in the majority of the studies. The results obtained presented inconsistent Acc values, ranging from 65–99%, being the

Ref. (Year)	Experimental design	Features	Classifier	Results
[63] (2015)	3 emotions, SEED	DEn, SP, statistics	DBN	DEn better than SP and statistics. Acc = 85%
[64] (2018)	4 emotions, two experiments: DEAP and SEED	DEn + others	GELM ¹	Acc = 69.67% (DEAP) and 91.07% (SEED)
[65] (2018)	3 emotions, SEED	DEn	HCNN ²	Best results in β and γ
[66] (2018)	3 emotions, 14 subjects, 64 EEG channels, film clips	DEn + others	GRSLR ³	Acc = 80.27%
[67] (2018)	3 emotions, two experiments: DEAP and SEED	DEn	—	Best results with SEED database
[68] (2018)	3 emotions, SEED	DEn, SP, statistics	DGCNN ⁴	DEn better than SP and statistics. Acc = 90%
[69] (2019)	3 emotions, SEED	DEn	LDA	Acc = 68%
[70] (2019)	2 emotions in patients with disorder of consciousness, 18 subjects, 32 EEG channels, videos	DEn	SVM	Acc = 91.5%
[71] (2019)	3 emotions, SEED	DEn	STNN ⁵	Acc = 84.16%
[72] (2019)	3 emotions, SEED	DEn	LR ⁶	Acc = 86%
[73] (2020)	3 emotions, SEED	DEn	MTL ⁷	Acc = 88.92%
[74] (2020)	3 emotions, SEED	DEn	CNN	Acc = 90.63%
[75] (2020)	3 emotions, SEED	DEn	CNN	Acc = 90.41%
[76] (2020)	High-low valence and arousal, DEAP	DEn + others	LORSAL ⁸	Acc = 77.17%
[77] (2020)	3 emotions, SEED	DEn + others	CNN	Acc = 99.7%
[78] (2020)	3 emotions, SEED	DEn + others	SRU ⁹	Acc = 83.13%
[79] (2021)	Valence and arousal, DEAP	DEn	CNN	Acc = 90.45% (valence) and 90.6% (arousal)

¹GELM: Graph-regularized extreme learning machine.
²HCNN: Hierarchical convolutional neural network.
³GRSLR: Graph regularized sparse linear regression.
⁴DGCNN: Dynamical graph convolutional neural network.
⁵STNN: Spatial-temporal neural network.
⁶LR: Linear regression.
⁷MTL: Multisource transfer learning.
⁸LORSAL: Logistic regression via variable splitting and augmented Lagrangian.
⁹SRU: Simple recurrent unit network.

Table 3.
Studies of emotions recognition from EEG recordings with predictability-based entropy indices (DEn).

frontal and parietal/occipital lobes the most relevant in emotional processes. With respect to the studies in **Table 3**, it can be noticed that the majority of them followed the same experimental procedure, but in this case, another public dataset different from DEAP was selected. Indeed, recordings from the SJTU Emotion EEG Dataset (SEED) were chosen and assessed for the detection of three emotional states, namely

Ref. (Year)	Experimental design	Features	Classifier	Results
[80] (2016)	5 emotions, 30 subjects, 6 EEG channels, video clips	MMSampEn ¹	—	Higher irregularity for higher arousal levels
[81] (2019)	2 emotions, DEAP	CMQSampEn ² , CMAAPE ³	SVM, DT	Acc = 86.35%
[82] (2019)	4 emotions, DEAP	WEn	SVM, FCM ⁴	Acc = 73.32%
[83] (2019)	2 emotions, DEAP	PerMin, DPerEn ⁵	KNN	Acc = 92.32%
[84] (2020)	3 emotions, 10 subjects, 14 EEG channels, video clips	WEn	ANN	Acc = 98%
[85] (2021)	3 emotions, SEED	MSPEn ⁶ + others	ARF ⁷	Acc = 94.4%
[86] (2021)	Enjoyment, 28 subjects, 8 EEG channels, art pieces	MSampEn	SVM, RVM ⁸	Acc = 91.18%

¹MMSampEn: Multivariate-multiscale SampEn.
²CMQSampEn: Composite multiscale QSampEn.
³CMAAPE: Composite multiscale AAPE.
⁴FCM: Fuzzy cognitive map.
⁵DPerEn: Delayed PerEn.
⁶MSPEn: Multiscale SpEn.
⁷ARF: Autoencoder based random forest.
⁸RVM: Relevance vector machine.

Table 4.
Studies of emotions recognition from EEG recordings with multiscale and multilag entropy indices.

positive, neutral and negative [63]. This database contained EEG recordings with 62 channels from 15 subjects during the visualization of film clips with emotional content [63]. The selection of the classification approaches was quite inconsistent across the different studies. However, it can be observed that deep learning approaches like convolutional neural networks (CNN) have been progressively introduced in the literature for their application in emotion recognition researches. The accuracy results reported in these works were between 68% and 99%. Furthermore, some of them demonstrated that DEn was more suitable than some linear metrics for the identification of emotions [63, 68].

Finally, **Table 4** shows the main works focused on the application of multiscale and multilag entropy approaches for detecting emotions with EEG recordings. As can be observed, the study of these indices has emerged in the last few years, especially since 2019 until nowadays. In these works, the number of emotional states studied ranged from 2 to 5, which is in line with the rest of entropy metrics evaluated. Furthermore, the signals from the DEAP database were also chosen by some of the studies included in the table. It can be noticed that the selection of the classification models was slightly inconsistent among the different studies, although SVM and deep learning approaches were the most selected. As in the previous cases, the final outcomes obtained presented accuracy values with a high variability, ranging from 73–98%.

4. General findings

The application of entropy metrics for the recognition of emotions from EEG signals has received increasing attention in the last years, reporting valuable insights

about the brain's performance under different emotional conditions. However, the high variability of the results obtained could be justified by various aspects. On the one hand, the experimentation is different for each study, since there are no gold standards of experimental procedures. In this sense, the number of participants and their gender, age, or cultural characteristics, are very inconsistent among studies, thus the results may not be representative of the whole population. In addition, the type of stimulus used for emotions elicitation (images, sounds, videos, etc.) is also inconsistent, since there is no consensus about which is the optimum option for triggering a strong emotional response [87]. The duration of the stimulus is another unclear point, thus different criteria are followed by each research group. Finally, although the locations of EEG electrodes are standardized, the number of EEG channels recorded is different in each experiment, ranging from 3 to 64. Moreover, some works assessed the signals corresponding to only one brain area, thus discarding the information that could be reported by the rest of regions.

All those experimental differences could bias the possibility of obtaining universal results that could be generalized to the whole population. As a consequence of all those discrepancies between experimental procedures, the studies presented in this manuscript should be carefully interpreted and compared. In addition, as not all the publications give a thorough description of their methodology, their experiments could not be reproduced by other research groups. Therefore, the assessment of signals extracted from publicly available databases, like DEAP or SEED, could eliminate this limitation, since the experimental procedure would be the same for different authors. In this sense, the reproducibility and comparability of the results obtained would be guaranteed, and the differences in the outcomes would directly appear due to the diversity of analysis methods and classification approaches.

The variability of the results could also be a consequence of the intrinsic differences of the entropy metrics evaluated. Indeed, regularity-based, predictability-based, and multiscale/multilag approaches evaluate the complexity of time series from different perspectives. Therefore, the application of either one or other type of entropy index on the same problem could report completely divergent outcomes. Nevertheless, instead of considering these inequalities as contradictory, it should be regarded as a sign of complementarity between the different entropy metrics. For instance, some characteristics of a nonlinear signal could be properly assessed with regularity-based entropies, and other dynamics would be better described by predictability and symbolic entropy measures. Consequently, the selection of either one or other type of entropy index should be done taking into account the information that is wanted to be extracted from a nonstationary time series, also considering that the combination of different entropies would report a more complete description of the nonlinear processes.

The promising outcomes presented in these studies make the entropy metrics a useful tool for the recognition of emotions from EEG recordings. However, the majority of the works are mainly focused on obtaining great classification accuracy values, for which advanced classification models with hundreds of input features are implemented. Despite providing notable numerical results in many cases, the combination of such a large amount of data in complex classification schemes derives in a total loss of clinical interpretation of the results. In this regard, information about which are the most relevant brain regions, or which EEG channels do a higher contribution to the classification model, cannot be obtained. Thus, it becomes impossible to make a thorough analysis of the brain's behavior under the emotional states detected. As a result, it would be interesting to modify some methodological aspects in this kind

of studies in order to ensure the clinical interpretation of the results and reveal new insights about mental processes under emotional conditions.

5. Conclusions

Given the nonlinear and nonstationary nature of the brain, entropy indices are suitable tools for a complete description of the brain dynamics in different scenarios, including the recognition of emotional states. This chapter summarizes the main recent contributions to the research field of emotions detection through the application of entropy indices for the analysis of EEG recordings. In this sense, regularity-based, predictability-based, and multiscale/multilag entropy approaches have demonstrated their capability to discern between different emotional states and discover new insights about the brain dynamics in emotional processes. Taking into account the valuable results obtained in the studies presented in this chapter, entropy metrics could become one of the first options to be considered in systems for automatic emotions identification from EEG signals.

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Conflict of interest

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